Case study examples of where AI, including optimisation, was used to help improve a development effort

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Five case studies to show how AI has been used to improve real development challenges

1. Optima HIV application in South Sudan
2. Improve performance-based financing in Zambia
3. Improve targeted supervision in South Africa
4. Answering health queries in Zambia using SMS
5. Rapidly expanding immunization coverage in Pakistan

Case Study Materials

Name

- 1. Sudan Allocative Efficiency Analysis.PDF
- 1. Sudan HIV Allocative Efficiency Study Final Report Dec 2016.pdf
- 1. Sudan poster final.pptx
- 2. Zambia PBF sampling PPT for DDS Training Big Data.pptx
- 2. Zambia Using supervised learning to select audit targets for PBF program...
- 3. South Africa big data analytics - full report.pdf
- 3. South Africa big data analytics - Policy brief.pdf
- 3. South Africa Big Data Analytics - PPT.pptx
- 4. Zambia AI helps to sort through text messages.pdf
- 5. Pakistan case study FRENCH.pptx
- 5. Pakistan case study_ENGLISH.pptx
- Agriclture Transformation in Africa.pptx

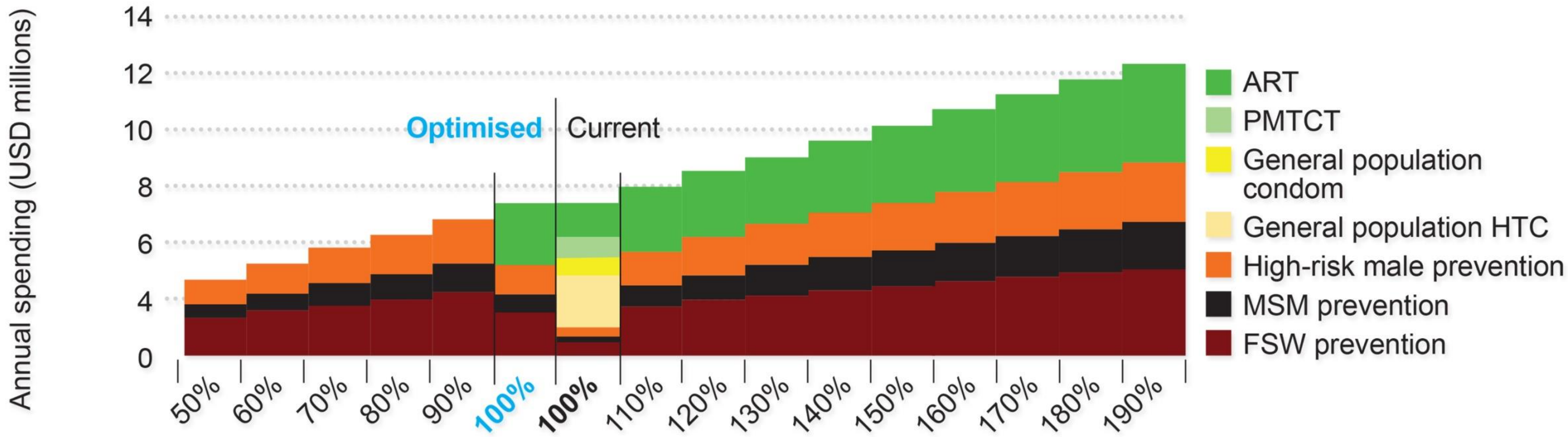
Each group, please read through the case study assigned to your group, and then answer these questions

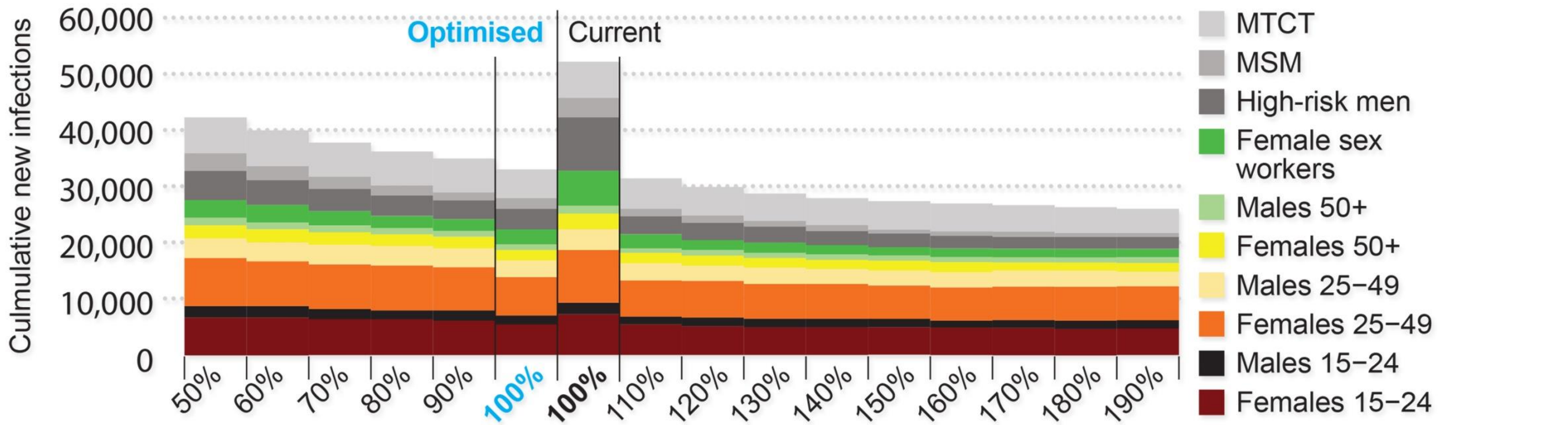
1. Describe how was AI used in the development solution
2. Identify the machine learning algorithm
3. What were the success factors that resulted in change
4. Any potential negative outcomes that needed to be mitigated

Please record your answers on a PPT (3 slides maximum) and bring it to the front on a flash-disk when your group is done

Optima HIV application in South Sudan

The case of SUDAN





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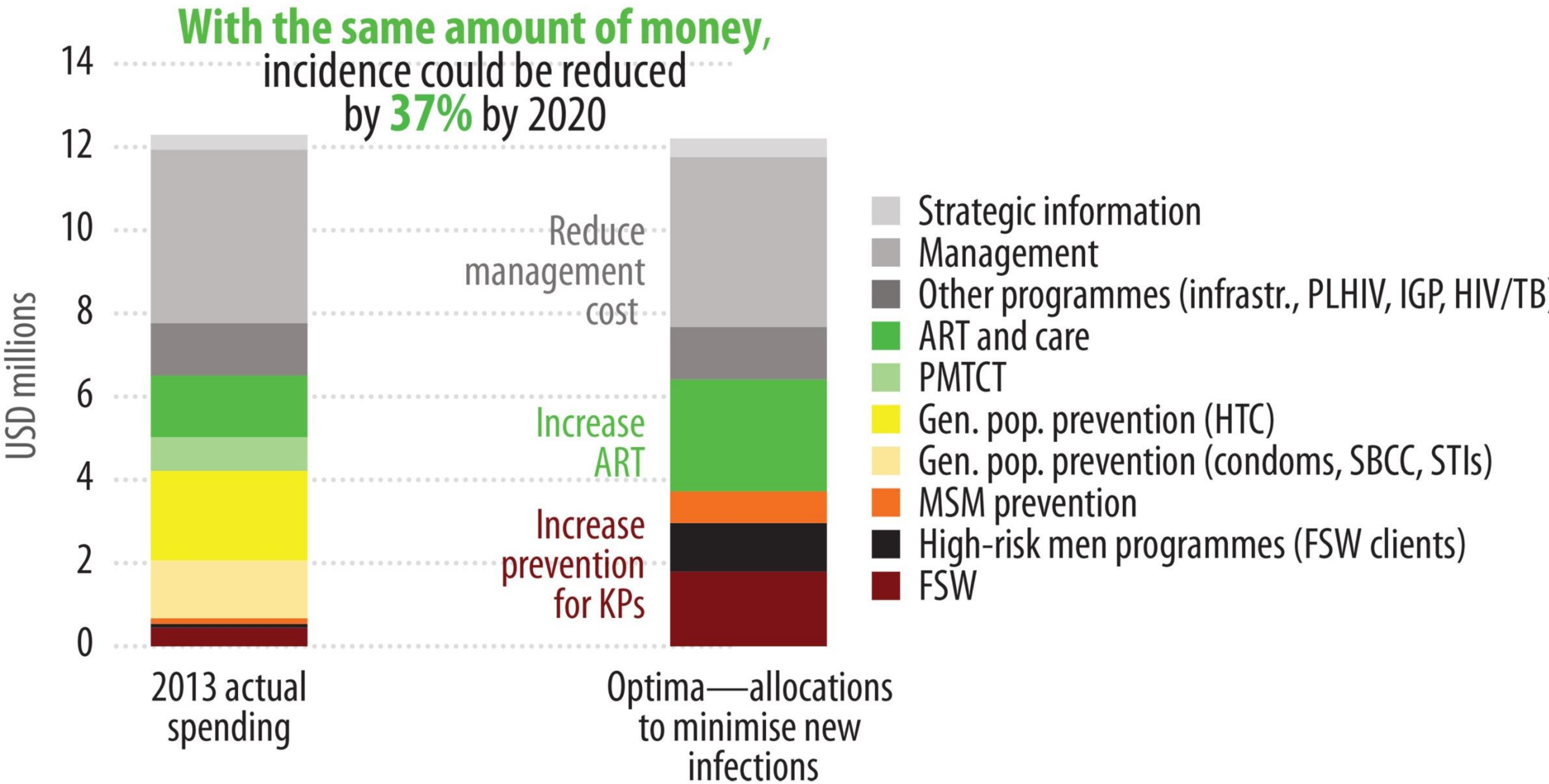
Sudan example, an FCV country with political and religious OPPOSITION TO HIV PROGRAMS

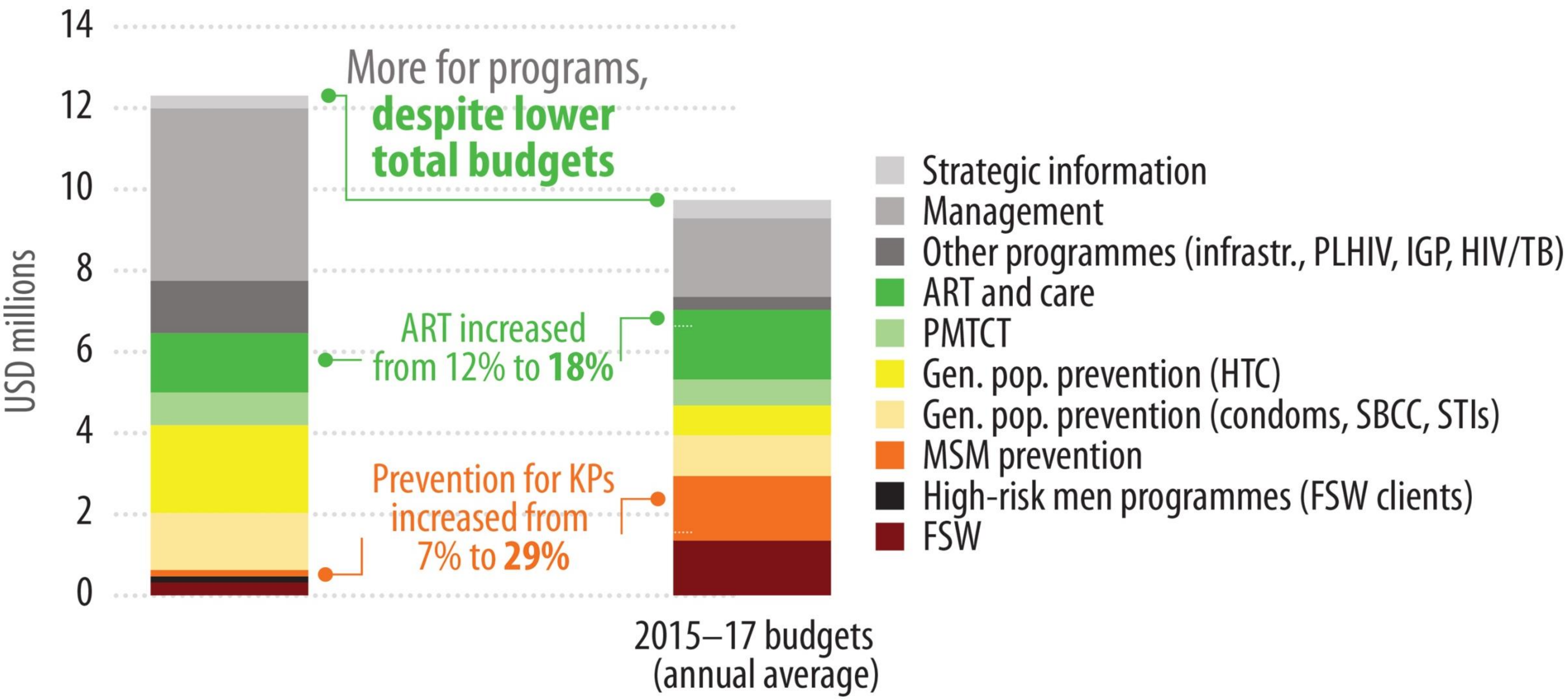
How were funds spent and where did the study recommend?

Spending pattern in 2013 and optimized allocations to minimize new HIV infections between 2014 and 2020, at 2013 resource level of USD 12.3 million



How did budgets actually change?

Reallocation of HIV resources in 2015–17 budget for the HIV response



2018 SKILLS BUILDING PROGRAM

BIG DATA, ARTIFICIAL INTELLIGENCE AND DECISION SCIENCE IN HEALTH AND NUTRITION

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USING SUPERVISED LEARNING TO SELECT AUDIT TARGETS IN PERFORMANCE-BASED FINANCING IN HEALTH: AN EXAMPLE FROM ZAMBIA

Jed Friedman

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What is Performance-based Financing (PBF)?

- Contracting mechanism that aims to increase the performance and quality of service providers.
- Offer financial incentives to health care facilities for provision of services
- Bonus payment based on a broad measure of quality

Monitoring of Performance-based Financing

- 3 layers of verification:
  - District or provincial supervisors visit all facilities on monthly or quarterly basis to confirm the accuracy of the reported quantity data.
  - District teams visit all facilities on a quarterly basis to complete a quality assessment.
  - Independent third-party conducts quarterly counter-verification visits to a sample of facilities.
- Aids in detection and determent of misreporting through random sampling of providers.
- Targeting of facilities varies from program to program, and has varied associated costs.

ZAMBIA'S PERFORMANCE-BASED FINANCING PILOT

2012-2014

Zambia’s Performance-based Financing Pilot

- To realign health financing towards outputs rather than inputs
- To address various health system concerns such as relatively low coverage of key maternal and child health services
- Pilot operated in public health centers in 10 rural districts, covering a population of 1.5 million (11% of Zambia’s population)
- 2 core features: financial rewards and equipment upgrades.

Zambia's Performance-based Financing Pilot

- Varying fee-for-service bonus payments for indicators measuring the quantity of 9 maternal and child health, and 10 structural and process quality domains.
- Health centers also received emergency obstetric care equipment.
- Participating health centers were subject to enhanced monitoring.
- Substantial financial rewards.

Zambia's Performance-based Financing Pilot

- Independent population surveys found gains in selected targeted indicators, such as rate of facility deliveries.
- Targeted indicators at already high levels of coverage saw little change (e.g. ante-natal care).
- Extensive auditing of reported data through continuous internal verification and a one-off external process.

2018 SKILLS BUILDING PROGRAM

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EVALUATING THE PERFORMANCE OF DIFFERENT CLASSIFICATION METHODS

Using data from the Zambia PBF pilot

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Data from Zambia PBF pilot

- Combined from facility reports and a dedicated facility survey (reproduction of external verification activities)
- 140 facilities: 105 primary health care centers in the 10 PBF pilot districts and 35 centers in another 8 non-pilot districts.
- Verification data were collected on the complete set of 9 incentivized indicators, for every calendar month of 2013.

- Binary measure equal to 1 if bonus payment based on the reported vs. verified data is ≥ 10% of the reported value.

Table 1: Overview of data from Zambia pilot

	Quarter			
	1	2	3	4
Percent over-reporting	18.6	15	22.9	20
Count	140	140	140	140
Percent of facilities over-reporting if also over-reporting in…				
Quarter 1	100	57.7	42.3	42.3
Quarter 2	71.4	100	66.7	47.6
Quarter 3	34.4	43.8	100	43.8
Quarter 4	39.3	35.7	50	100

Table 2: Distribution of facilities that over-report

	N	Percent
Never	81	57.9
One quarter	32	22.9
Two quarters	12	8.6
Three quarters	9	6.4
All four quarters	6	4.3

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Classification Methods

Sampling-based approaches (overall sample size: 28):

- 50% clinics chosen at random
- Stratify by district, then select 50% clinics at random
- Random 50% of clinics that over-reported in prior quarter, plus random 50% from the remaining clinics
- Select up to 28 clinics that are prior offenders, randomly sample from remaining facilities to achieve target number.

Accuracy of sampling-based approaches reported as averages of 1000 independent sampling iterations without replacement

Classification Methods

Alternate approaches (including supervised machine learning):

- Naïve Bayes
- Logistic Regression
- Support Vector Machines
- Random Forest

Supervised learning are a class of machine learning algorithms that use labeled examples to infer a relationship between input and output variables, and then use that inferred relationship to classify new examples

Supervised machine learning for PBF data

- For verification in PBF:
  - Input: subset of facility-specific data points
    - 9 quantity measures that were rewarded in the RBF program
    - District identifier
    - Categorical variable indicating treatment arm from related audit experiment
  - Output: binary indicator for whether or not a facility over-reported
- Algorithm learns which facilities are at risk of over-reporting.
- Applies this learning to predict this risk for other facilities not included in the training data.

Naïve Bayes

- Calculates the probability of an input (or specific set of predictive features) belonging to each class (over-reported, or not), and then chooses the class with the highest score.
- Assumes strong independence between these predictive features. Correlations between features, if any, are disregarded.

Logistic Regression

- Uses a logistic function at its core to estimate a relation between the binary classification (over-reported or not) and its possible predictors.
- Assumes that the input space can be partitioned by a linear boundary, separating the data into two classes

Support Vector Machine

- Defined by a hyperplane that maximizes the separation between the two classes.
- Maximizes the margins from both categories, such that the distance from the boundary to the nearest data point on either side is the largest.
- Once optimal hyperplane is found using labeled training data, features from the test set can then be classified into their respective categories by determining whether they fall on one side of the boundary or the other.

Random Forests

- Averages multiple decision trees, trained on different parts or features of the same training set, with the goal of reducing variance.
- Individually, predictions made by decision trees may not be accurate
- But combined together on different features they achieve higher predictive power

Choosing the appropriate machine learning technique

- Size of training data set
- If there is a need to learn interactions between the various features or whether can they be treated as independent variables
- Whether additional training data may become available in the future and would need to be easily incorporated into the model.
- Whether the data is non-parametric and not linearly separable.
- Whether overfitting of the model to the training data is expected to be a problem.
- Requirements in terms of speed, performance and memory usage.

Choosing the appropriate machine learning technique

- Small training sets: use Naïve Bayes. Logistic Regression has tendency to overfit.
- Larger training sets:
  - Roughly linear data features: Logistic Regression. Robust to noise, can avoid overfitting, allows updates. Also can give probability output (instead of classification).
  - Non linearly separable: Support Vector Machines (SVMs). High accuracy, works with high dimensional spaces, avoids overfitting. Cons: Memory intensive, hard to interpret, challenging to tune for optimal performance.

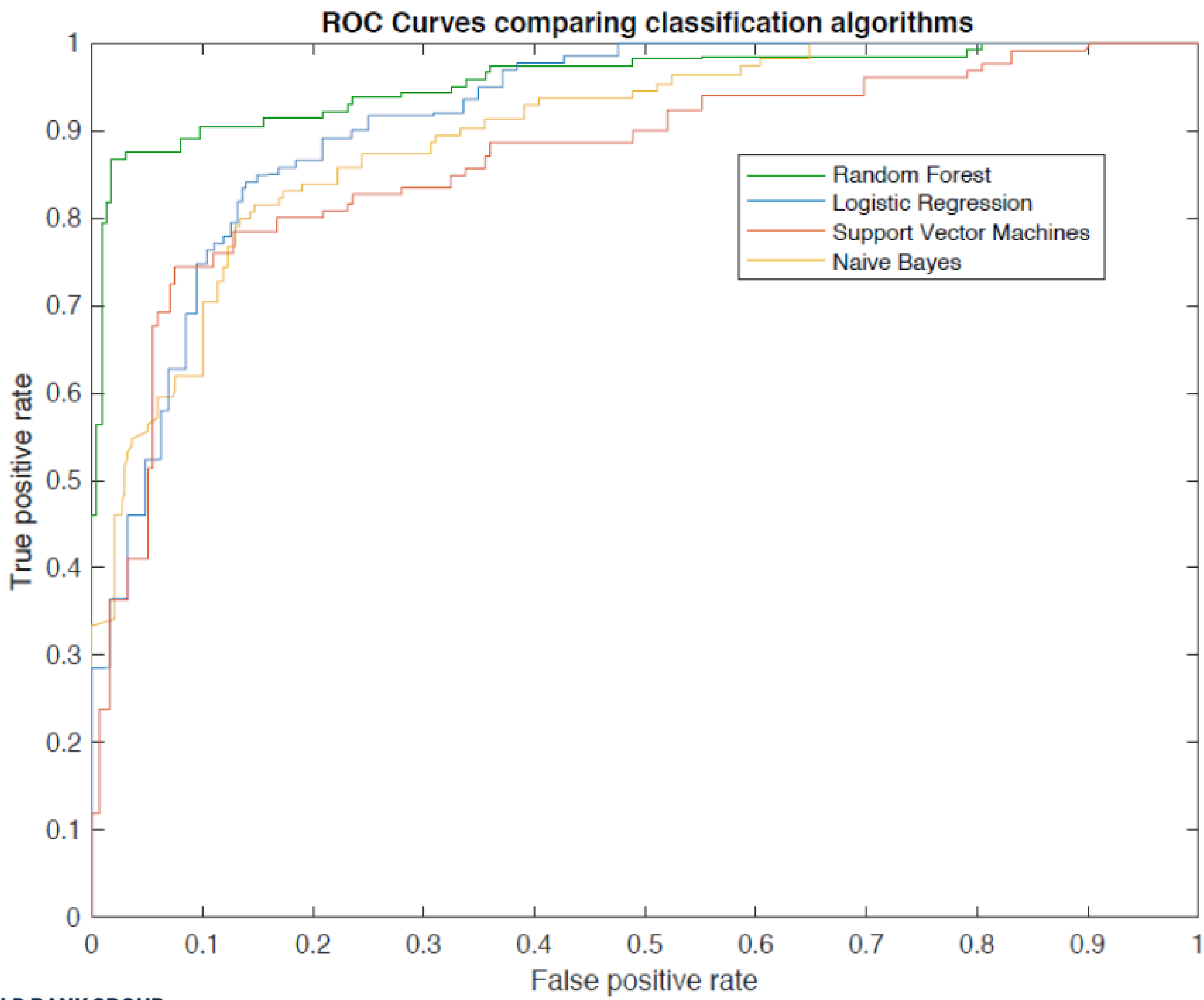
Advantages of tree ensemble-based learning methods

- Do not expect linear features or even features that interact linearly (unlike with Logistic Regression)
- Handle high dimensional spaces as well as large number of training examples (advantage over SVMs)
- Random Forest methods:
  - Are fast and scalable (unlike SVMs)
  - Avoid overfitting
  - Don’t require tuning of parameters

Analysis of methods: Performance metrics

- Prediction accuracy
- F-score
- Area under the ROC
- Average precision rate
- Root mean squared error (RMSE)

Results


ROC Curves comparing classification algorithms
True positive rate
False positive rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Random Forest
Logistic Regression
Support Vector Machines
Naive Bayes

Results

Table 3: Normalized scores of learning algorithms across five performance metrics

Model	Accuracy	F-score	ROC area	Avg precision	RMSE
Logistic Regression	0.584	0.509	0.728	0.627	0.603
Naïve Bayes	0.552	0.425	0.583	0.523	0.488
SVM	0.647	0.651	0.783	0.691	0.501
Random Forest	0.866	0.821	0.901	0.896	0.817

Note: scores normalized to range from 0 (worst) to 1 (best).

Results

Table 4: Prediction accuracy performance of different approaches

Approach	Prediction of over-reported event			
	Q1	Q2	Q3	Q4
Sampling approaches				
SRS	18.77%	14.98%	22.56%	20.04%
SRS with district stratification	18.83%	15.21%	23.22%	19.9%
SRS of offenders & non-offenders	-	34.5%	36.5%	27.87%
SRS of only offenders	-	44.5%	42.19%	38.81%
Supervised learning				
Logistic Regression	58.42%	32.84%	31.28%	34.76%
Naïve Bayes	55.24%	46.15%	32.05%	41.3%
SVM	64.75%	58.02%	49%	52.26%
Random Forest	86.6%	89.18%	84.92%	77.31%
Random Forest with district	87.84%	86.19%	81.99%	76.96%
Random Forest with intervention	85.08%	82.29%	77.83%	73.08%

Note: Accuracy is calculated as average of 1000 independent sampling without replacement iterations for SRS, and 10-fold cross-validation for supervised learning.

Conclusions

- Over-reporting is a highly non-linear function of covariates
- Predictions from traditional regression analysis will not be particularly accurate
- Supervised learning approaches, such as Random Forest, could substantially improve the prediction accuracy of counter-verification in PBF
- Hence also increase the cost-effectiveness of verification.
- These methods are operationally feasible, especially in settings with electronic routine reporting systems

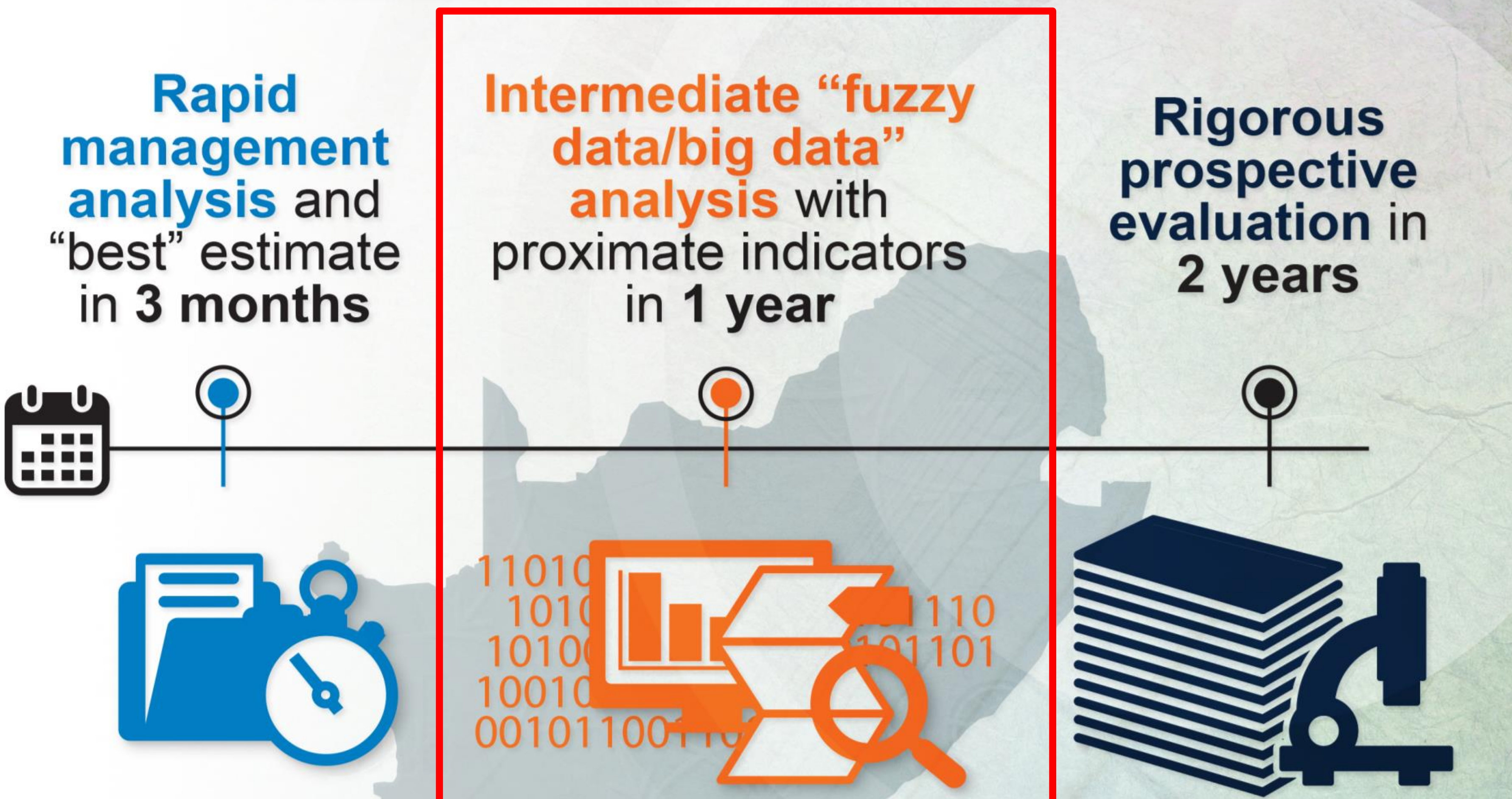
IMPROVE TARGETED SUPERVISION IN SOUTH AFRICA

20% of people GLOBALLY on HIV treatment, are in South Africa

the CHALLENGE

1. Do **viral load detection rates** differ across the country?
2. Do **viral load suppression rates** differ across the country?
3. Are these differences **spatially** distributed?
4. What can be done to **change** it?

Three-phased approach to support SA's HIV treatment program improvements



Testing different treatment adherence support interventions at individual, clinic and district levels

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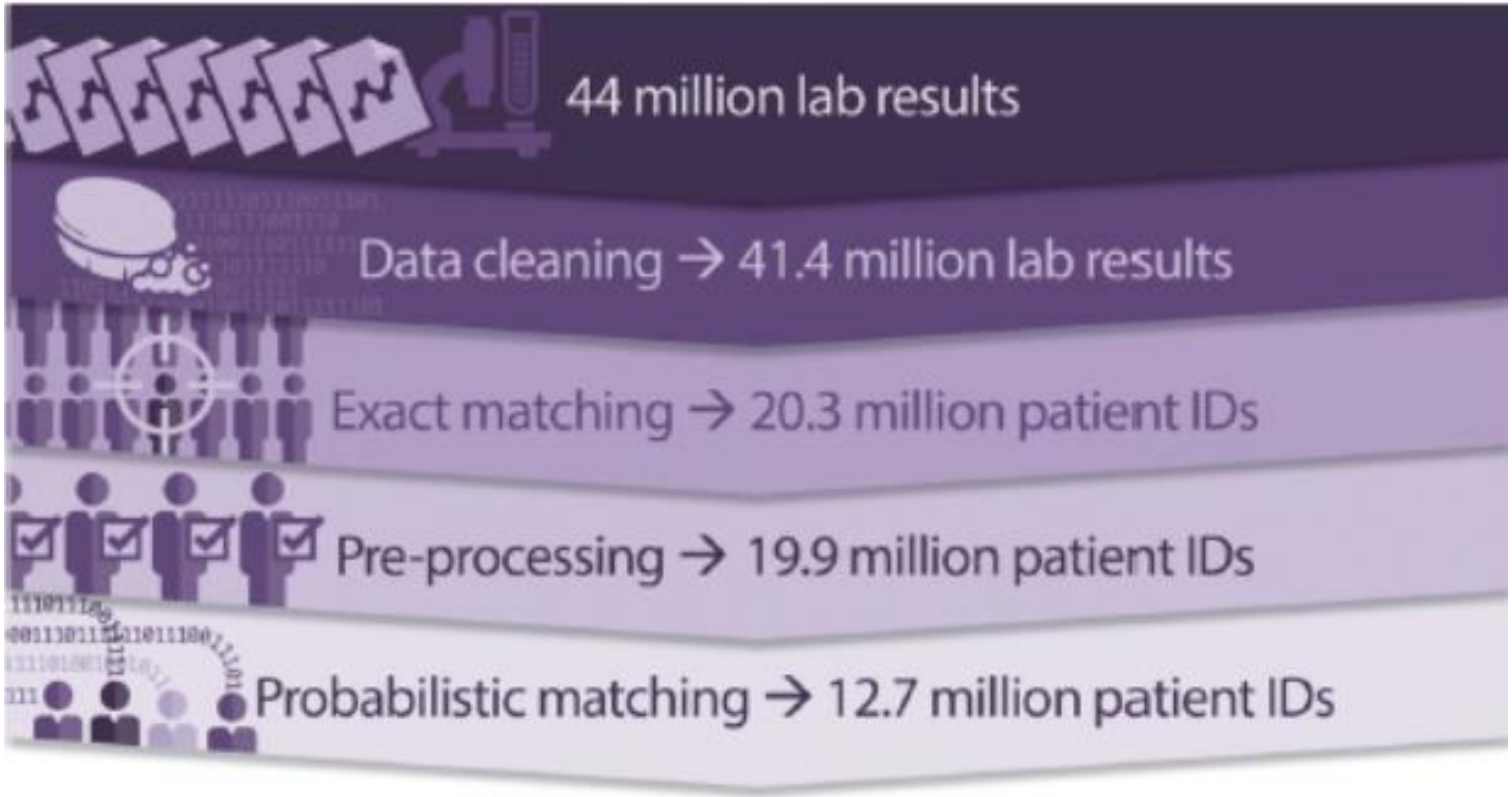
Big Data Analysis: 3 routine, incompatible datasets, Over 100 million records, in total



Linked to District Health Information System (facility level data, AND Individual HIV client registers)

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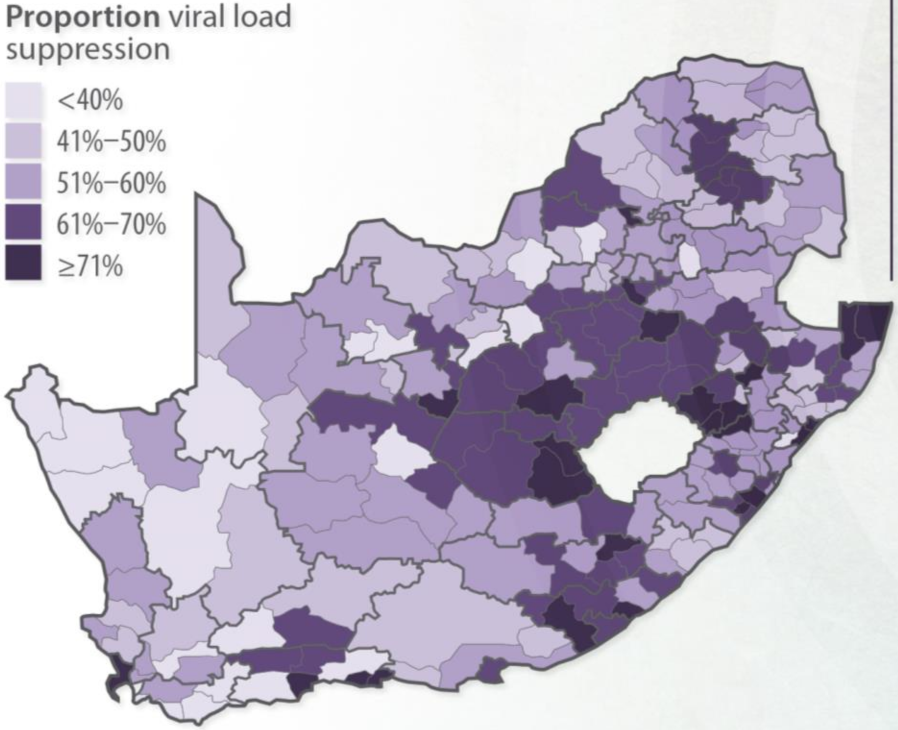
YES, Substantial Variations in Viral Load Detection Rates and Viral Load Suppression Rates

Identifying **Successes**

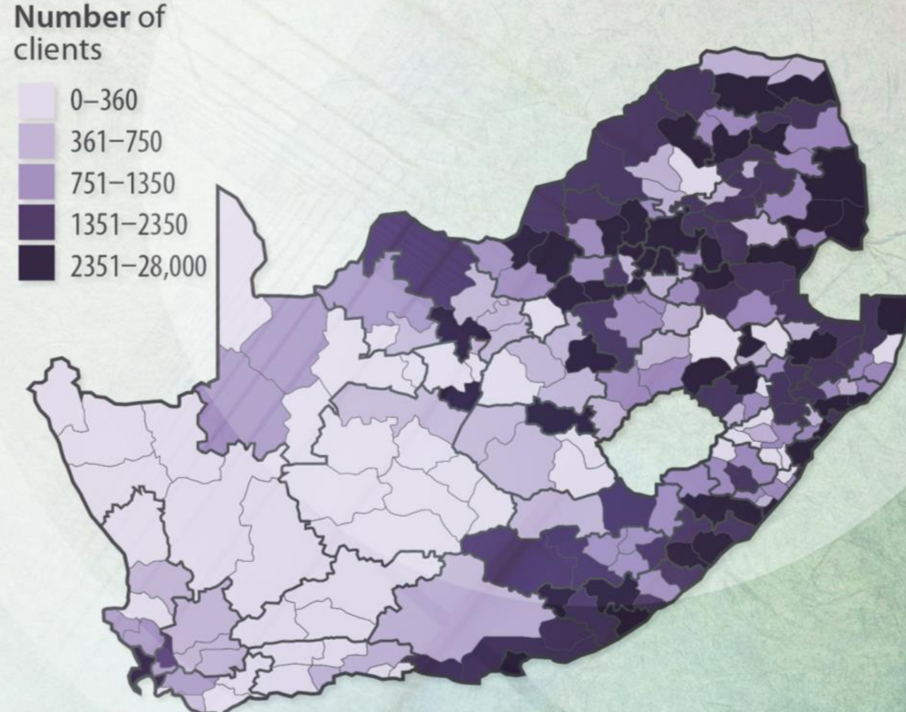
Proportion of ART clients with known VL suppression (<400 cp/ml)



Can we learn from the dark-shaded sub-districts?

Identifying **Failure**

Number of ART clients with high VL (>1,000 cp/ml)



Low hanging fruit for better adherence support

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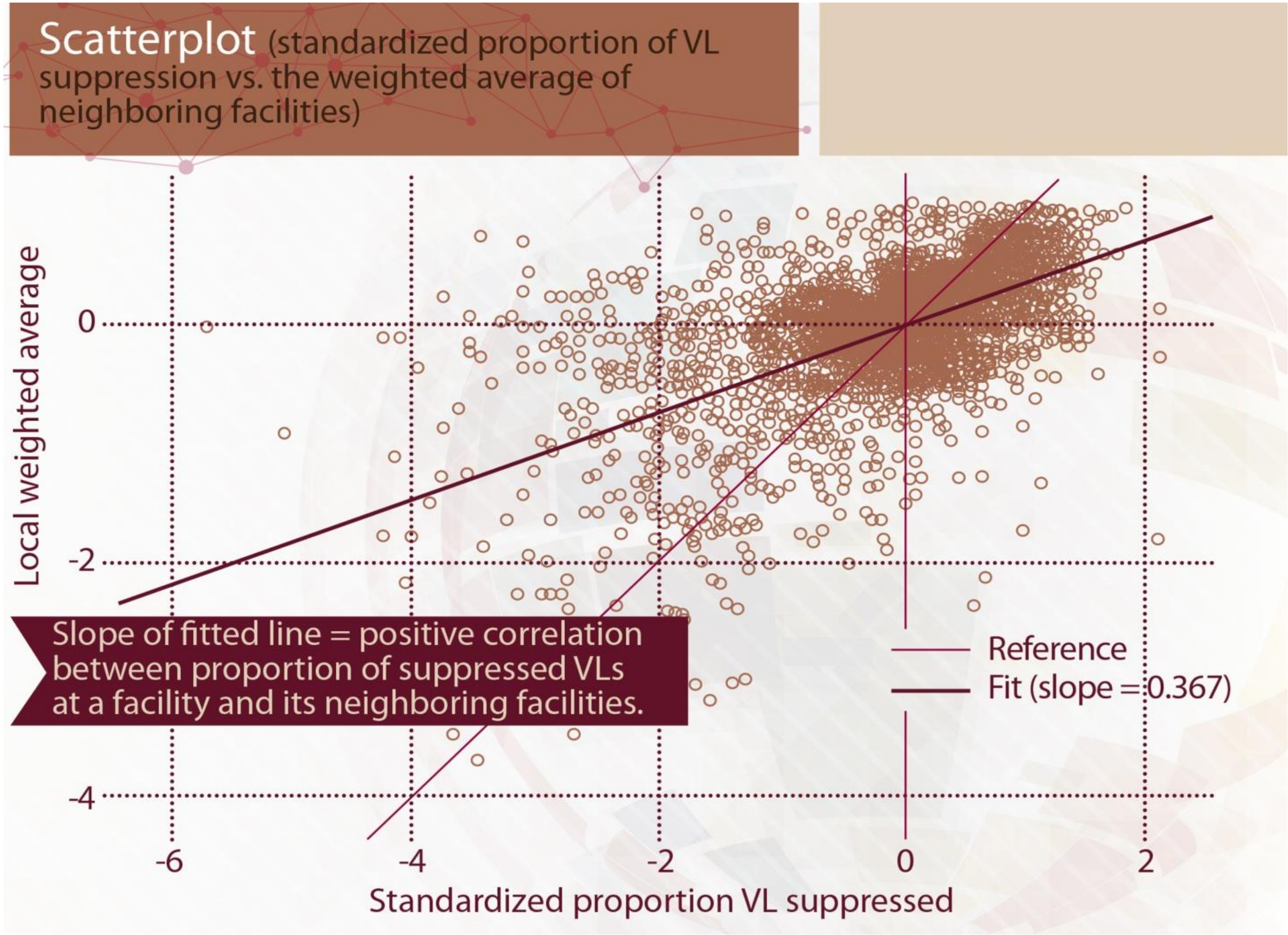
YES, the facility-level performance is spatially correlated



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Improve agricultural intervention targeting in Africa

Catalyzing Inclusive Agricultural Transformation in Africa

A Machine Learning Approach

Sam Fraiberger (WB)
Marelize Görgens (WB)
Clara Ivanescu (WB)
Andrew Longosz (WB)
Shaffiq Somani (WB)
Tushar Malik (WB)
Theo Hawkins (WB)
Lakshmi Subramanian (WB/NYU)
Ananth Balashankar (NYU)
Eric Deregt (NYU)
David Wilson (BMGF)

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Key Questions concerning agricultural transformation

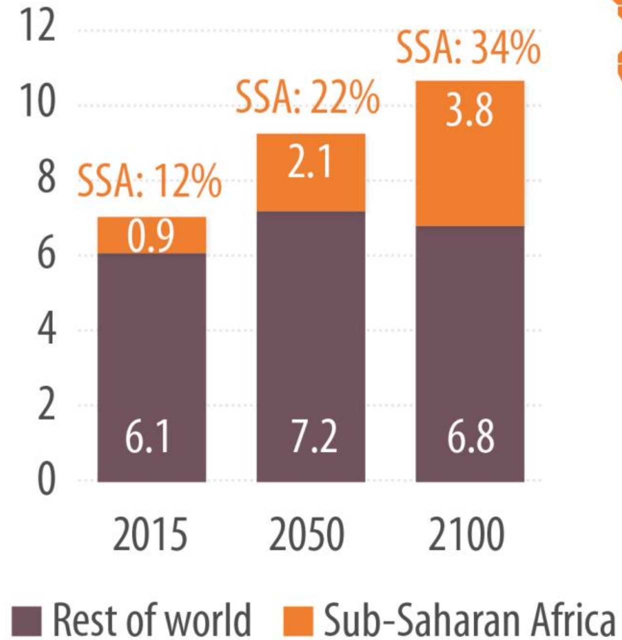
AGRICULTURAL TRANSFORMATION

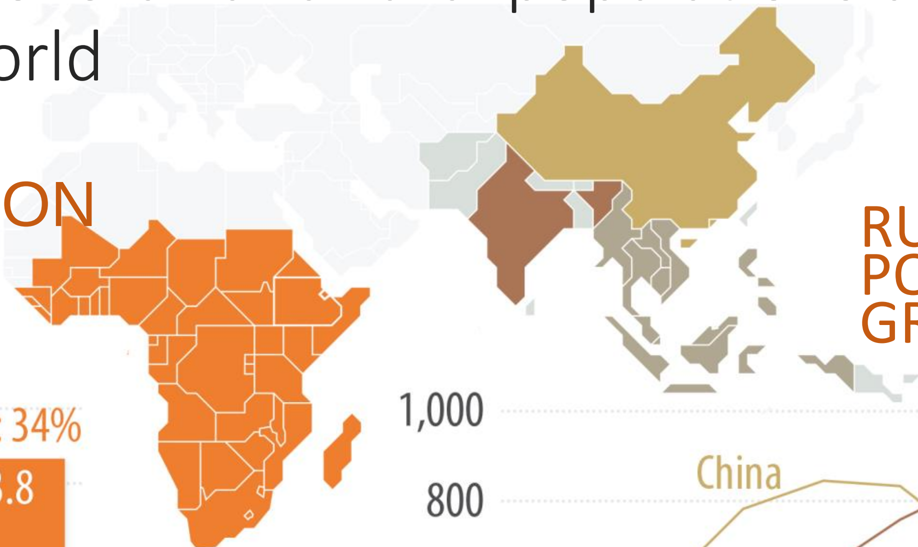
- Use agricultural transformation inputs to define clusters of households of farmers that are associated with differences in productivity and income growth
- Are clusters consistent over time?
- How can agricultural transformation within a cluster be optimized?
- Are there pathways for progress between clusters?
- Do these differ within and between countries (Ethiopia and Tanzania)?

Development context in Africa is rapidly changing…

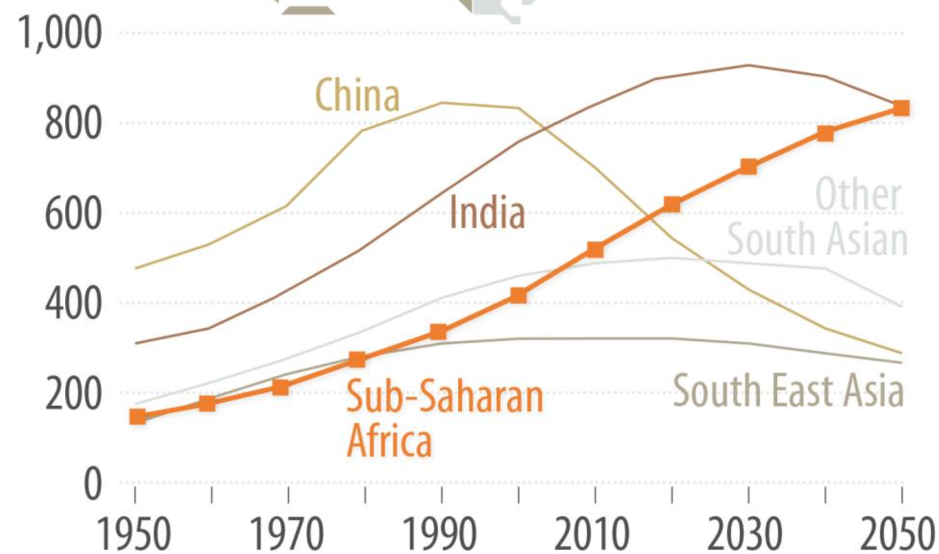
- …increases in overall and rural populations unlike in other parts of the world

SSA POPULATION GROWTH





RURAL POPULATION GROWTH



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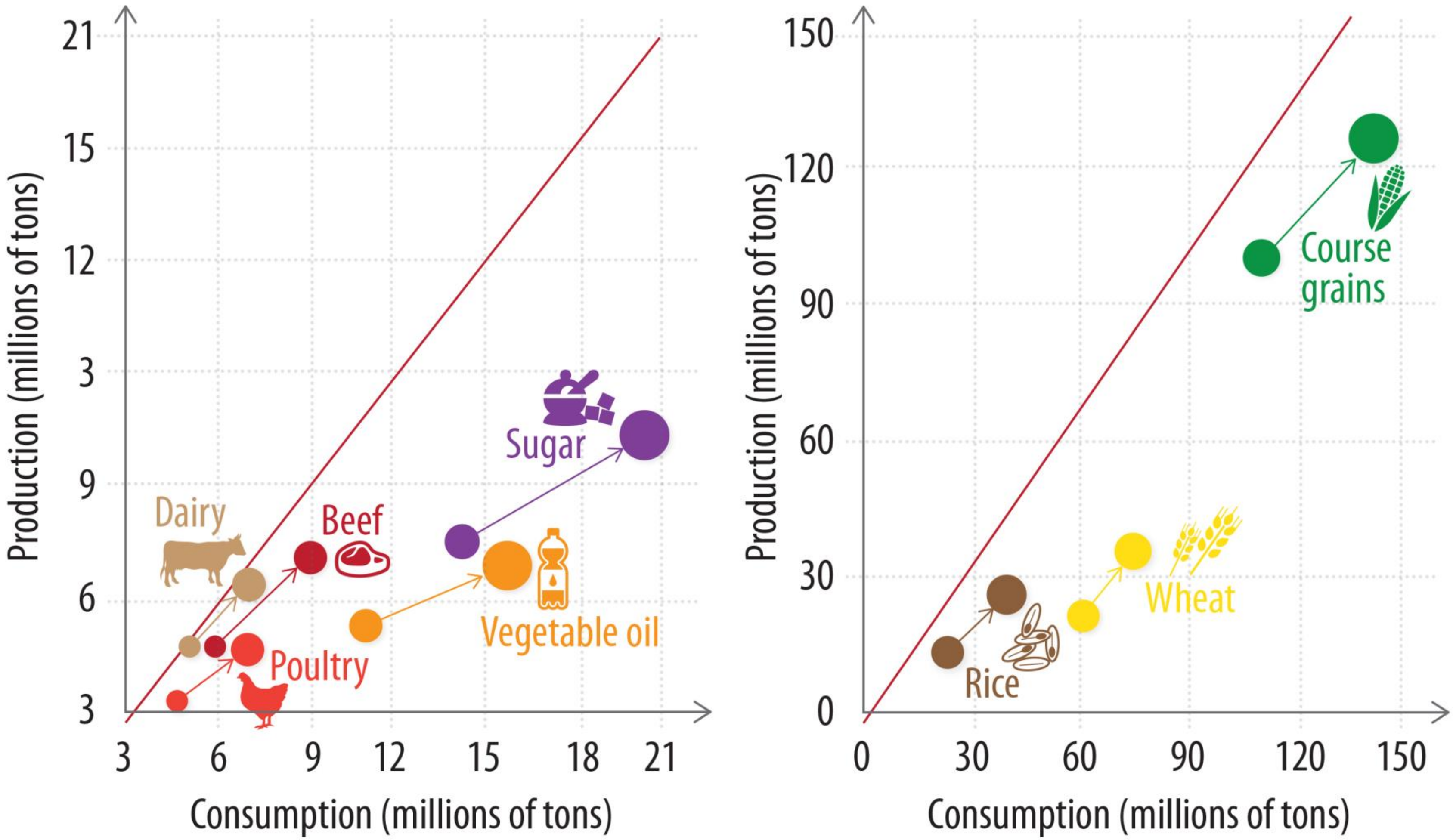
Source: Jayne et al. (2016)

Because of population growth, increased need for food in Africa

- Projected trends in sub-Saharan African commodity production and consumption (2013–2023)



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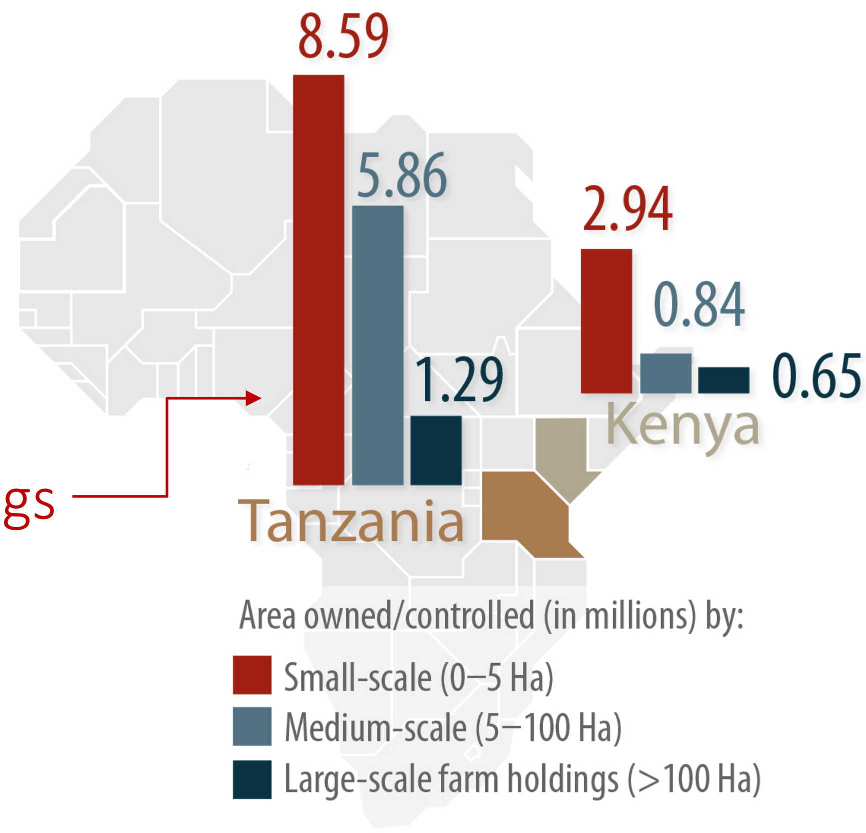
Source: FAO: acknowledgements to Holger Matthey/FAO, August 2014

Despite some transformation, agriculture in Africa struggles

Agriculture remains the predominant sector of the economy 25% of GDP in SSA

- Most food insecure continent with high malnutrition
- Low levels of agricultural productivity and a worsening food trade balance
- Still high levels of subsistence agriculture with small landholdings



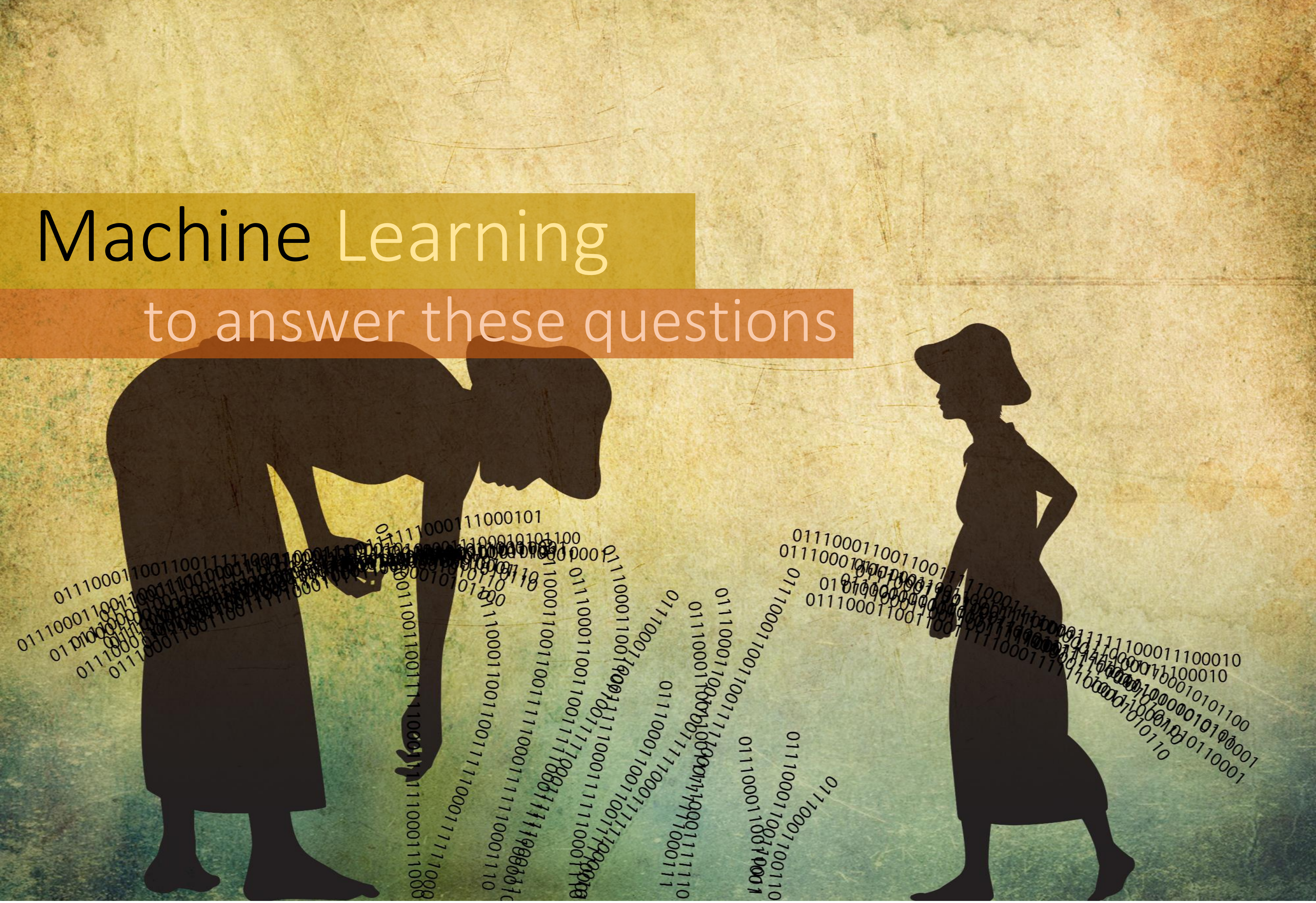
Source: Jayne et al. (2016)

To achieve agriculture's potential, transformation is essential

- Measured through:
  - Increases in farmers' income, competitiveness and productivity
  - Better food security
  - Better access to social services (education and health)
- Stronger agricultural growth facilitates human capital growth and economic growth

Machine Learning

to answer these questions



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Used the LSMS-ISA dataset

- Longitudinal survey of farmers; links farm and non-farm activities
- BMGF funding for its implementation
- 8 Countries:
  - Burkina Faso (1 wave)
  - Malawi (2 waves)
  - Niger (2 waves)
  - Tanzania (4 waves)
  - Ethiopia (3 waves)
  - Mali (1 wave)
  - Nigeria (3 waves)
  - Uganda (4 waves)

- Initial focus on Ethiopia:
  - ~3,500 households surveyed over time (2011–12, 2013–14, 2015–16)
  - ~1,500 features per households
- Same approach expanded to Uganda and Tanzania to assess differences between countries

Ethiopian ATA
Agricultural Transformation Agency
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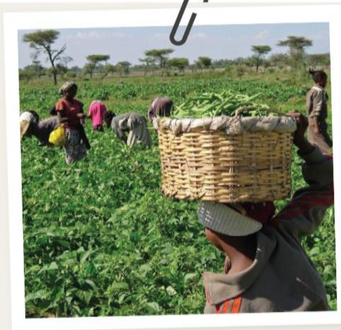
What can we measure from these data?

OUTCOMES:

- Evidence of agricultural transformation and how they change over time
  - Crop sales, crop sales growth, productivity, household expenditure, food expenditure diversification, and food security
  - Education and health service access



INPUTS…

- through which to achieve agricultural transformation and how they change over time: Household, farmer and farming practices characteristics
  - Some inputs can be modified through short term policy actions (actionable) and others not (non-actionable):

ACTIONABLE

- Accessibility (distance to road/market/population center)
- Agronomic practices (crop diversification, fertilizer, seeds type, irrigation, damage prevention, land certificate, extension program)
- Equipment (axe, oxen, plough, sickle)
- Rented factors (credit, hired labor)
- Shocks (health issues, unexpected price changes)
- Financial inclusion (access to credit, bank accounts and savings)

NON-ACTIONABLE

- Demographics
- (age, marital status, region of origin)
- Physical conditions (elevation, temperature, precipitation, rooting conditions, variations in greenness)

Machine Learning Results: Ethiopia

▶ Semi-supervised ML approach

A. Look at **correlation between outcomes**: are they cross-correlated to determine if outcomes should be measured separately or together

B. Look at **correlation between outcomes and input variables**

C. Identify **highly-correlated input variables**

D. **Cluster farmers** using k-means clustering

In k-means clustering: Finds groups of farmers such that the values of the farmers across the 7 selected input variables are similar to others in the group and different to farmers in other clusters, i.e., minimize Euclidian distance to the centre and maximize distance between groups.

Additional step: Weight each input by its average correlation across outcomes variables

Look at most important variable/s within each cluster

Look at pathways and thresholds to move between clusters

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Are agric. transformation outcomes in Ethiopia correlated with each other?

	Children Education	Crop Sales	Crop Sales Growth	Expenditure	Food Expenditure Diversification	Has Medical Assistance	No Food Deficiency
Children Education		0.011	-0.044	0.141	0.115	0.054	0.108
Crop Sales			0.45	0.273	0.047	0.062	0.174
Crop Sales Growth				0.008	-0.032	-0.023	0.043
Expenditure					0.074	0.068	0.228
Food Expenditure Diversification						0.086	0.09
Has Medical Assistance							0.005
No Food Deficiency							

- Varying levels of correlation between outcomes: mostly low
- So, need to **evaluate each outcome separately** in terms of its correlation with inputs

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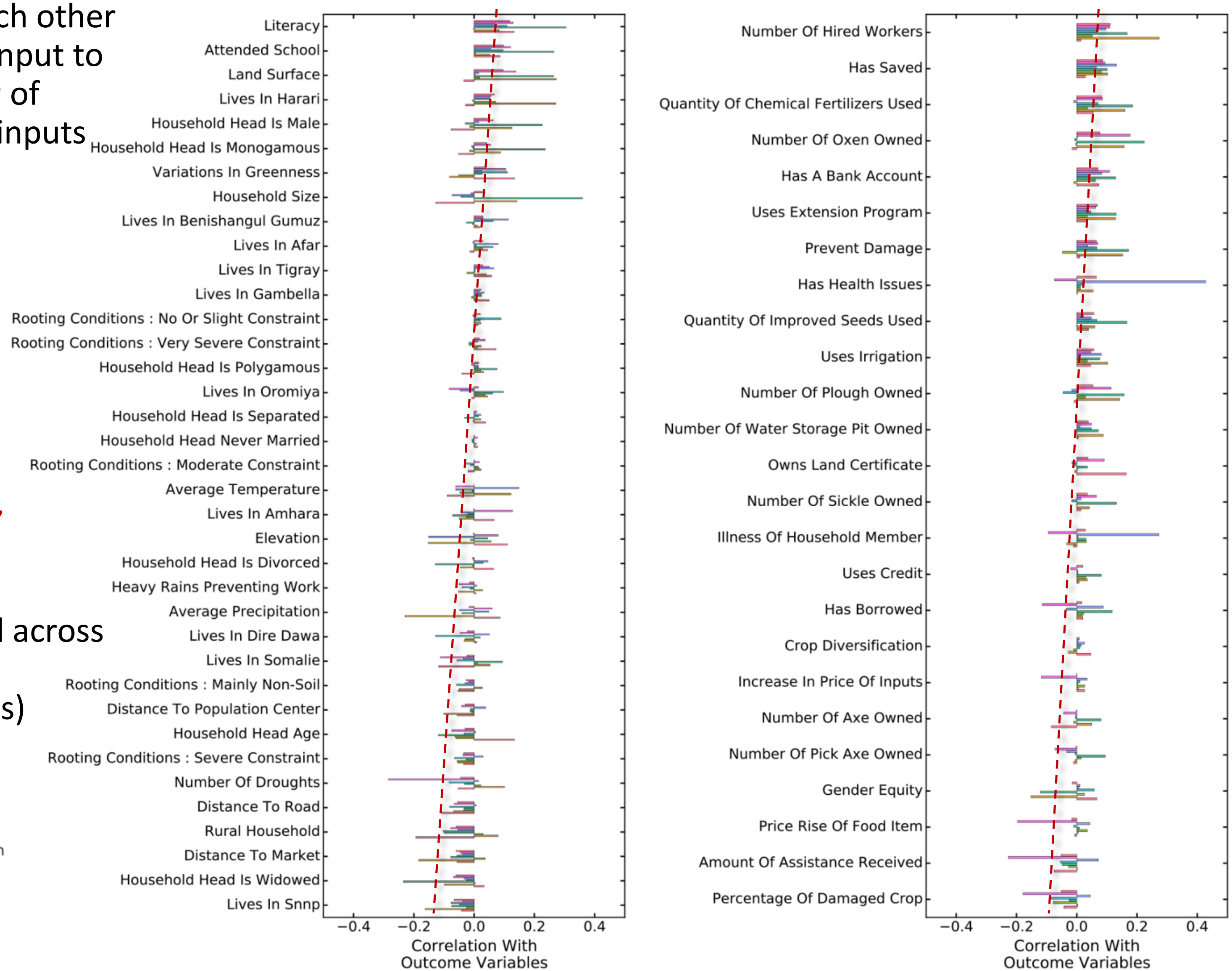
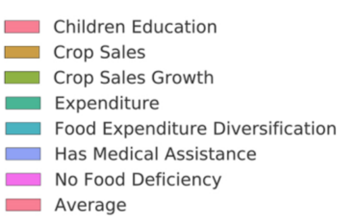
First, determine cross-correlation between inputs and selected outcomes

- Many inputs are cross-correlated with each other – can choose one input to represent a cluster of closely-correlated inputs
- Cross-correlations between inputs and outputs are low
- Most predictive inputs have a similar directional effect across outcome variables, yet their impact varies
- Similar results hold across years (3 waves of analysis)

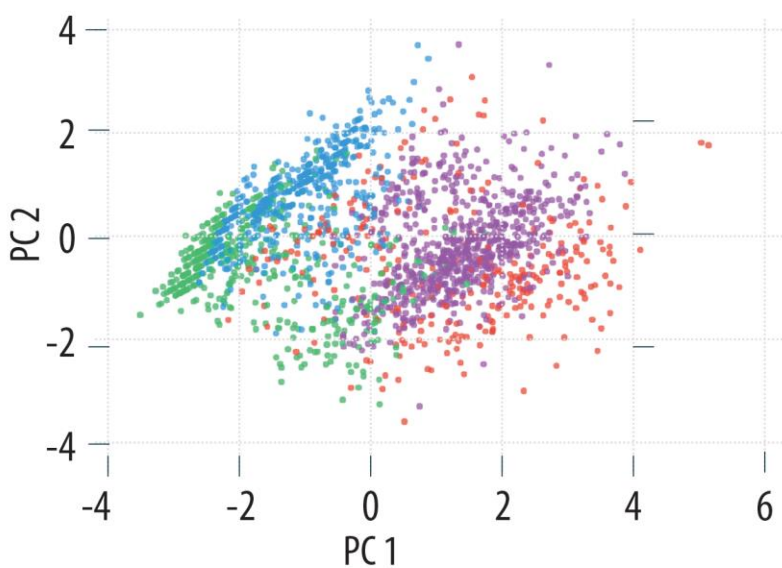
Non-actionable inputs

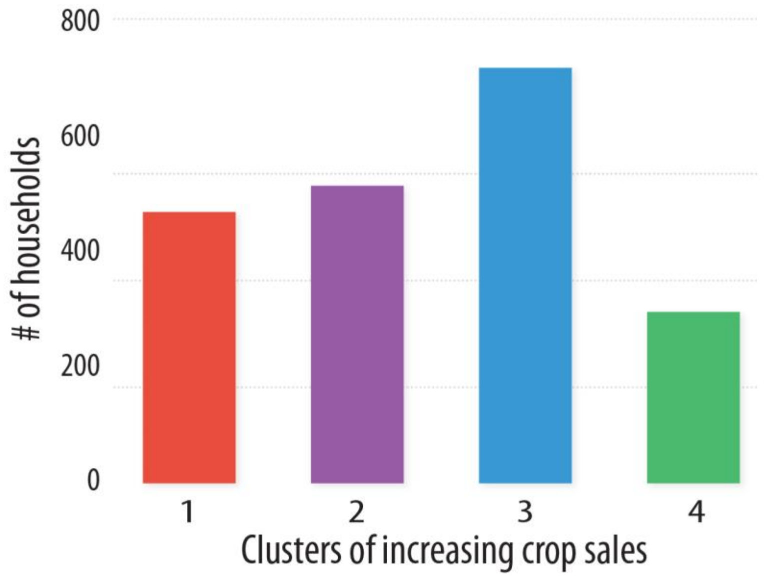
Actionable inputs



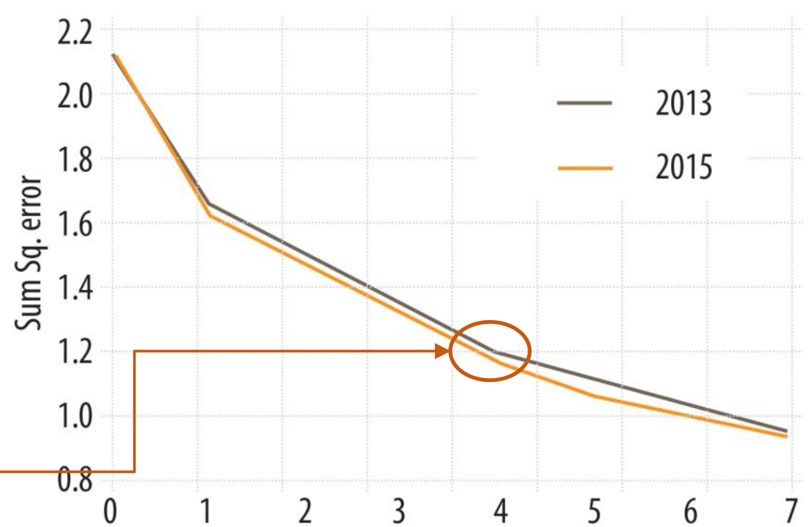


K-means clustering results



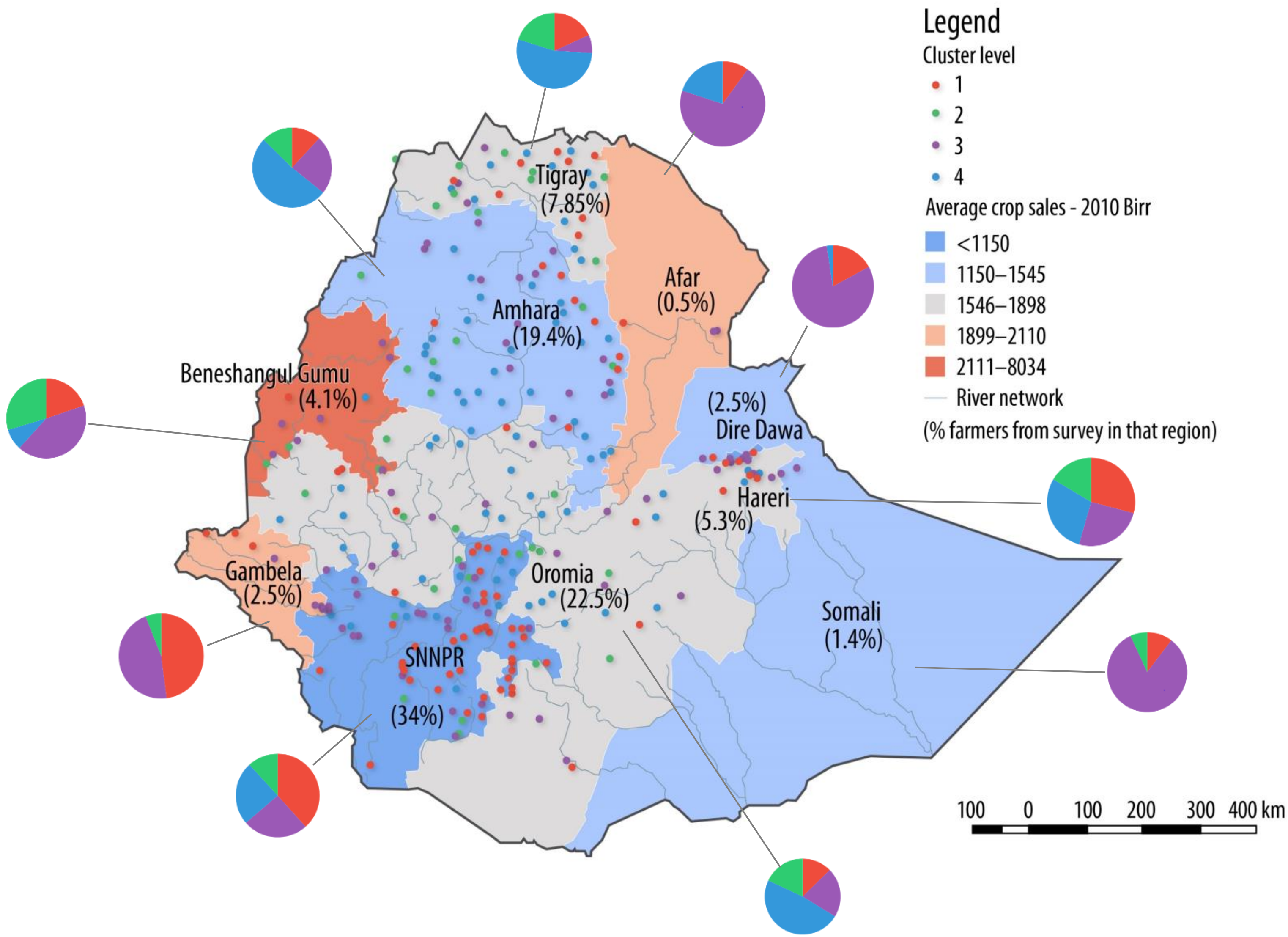


- K-means clustering achieves desired outcome: clusters farmers based on their own unique set of actionable variables most correlated with outcomes and not with other input variable



- Clustering consistent over time
- We pick: number of clusters = **4**

Where are the clusters?



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Initial policy observations

FOR LOW INCOME CLUSTER
Expand equipment (oxen and ploughs) and crop diversification

FOR MIDDLE INCOME CLUSTERS
Improve all the other features

FOR HIGH INCOME CLUSTER
Increase hired workers and increasing savings

Optimizing income in a cluster

Most impactful input: Comparison across countries

	CLUSTER 1	CLUSTER 2	CLUSTER 3	CLUSTER 4
Most Impactful Input in Ethiopia	Increase farmers' savings	Increase # of hired workers	Increase # of hired workers	Increase # of hired workers
Most impactful input in Tanzania	Increase # of animals	Increase quantity of pesticide	Increase # of animals	Increase # of animals
Most impactful input in Uganda	Increase # of days for which workers are hired	Increase crop diversification	Increase number of days for which workers are hired	Increase crop diversification
Other Impactful Input in Ethiopia	Increase # of oxen owned	Obtain water storage pit	Increase quantity of chemical fertilizers used	Use extension program
Other impactful input in Tanzania	Increase quantity of pesticide	Decrease crop diversification	Increase quantity of pesticide	Increase quantity of pesticide
Most impactful input in Uganda	Increase quantity of pesticides used	Increase quantity of pesticides used	**Increase crop diversification**	Increase # of tools owned

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Pathway analysis

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Which pathways do we actually observe?

	CLUSTER 1	CLUSTER 2	CLUSTER 3
Rate of moving over time: % Households that moved to a higher cluster (from 2011 to 2013 or 2013 to 2015)	**23.6%**	**32.9%**	**17.6%**
1st most impactful input (from optimisation analysis)	Has saved	Number of hired workers	Number of hired workers
LIFT FACTOR 1: By how much an increase in input will be associated with an increase in the probability of moving to a higher cluster	No temporal data available (only collected for 2015 wave)	Farmers in this cluster who increase the hired number of workers have a **34%** higher probability of moving to a higher cluster	Farmers in this cluster who increase the hired number of workers have a **32%** higher probability of moving to a higher cluster
Other impactful input (also from optimisation analysis)	Number of oxen owned	Number of water storage pit owned	Quantity of chemical fertilizers used
LIFT FACTOR 2: By how much an increase in input will be associated with an increase in the probability of moving to a higher cluster	Farmers in this cluster who increase the hired number of workers have a **7%** higher probability of moving to a higher cluster	Farmers in this cluster who acquire more water storage pits have a **18%** higher probability of moving to a higher cluster	Farmers in this cluster who increase the chemical fertilizers that they use have a **12%** higher probability of moving to a higher cluster

Summary

Summary

- We found a robust clustering of farmers in all 3 countries
  - Characteristics associated with clustering in each country differ dramatically
  - Clusters can be described as different phases of the agricultural transformation process
  - Describes a pathway towards agricultural transformation
  - Each inputs suggest a prioritized policy action at different phase of the transformation process

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Summary

- Most impactful input differs significantly between tries

- Reasons include:
  - Differences in correlations between inputs and outcomes
  - Differences in farmer characteristics
  - Differences in data
  - Differences in underlying characteristics of population

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Summary

- Cross-country comparisons limited by lack of common measurement of some key inputs.
- Yet, some patterns emerge:
  - clustering analysis clearly shows that different farmers profiles exist across countries, suggesting to design cluster level policies
  - inputs which are the most impactful of an increase in crop sales vary across clusters, supporting the implementation of cluster-level policies, rather than population level policies
  - across countries, most predictive variables are hiring workers, usage of fertilizers or pesticides, animals, tools, irrigation, or animals; yet their relative importance across clusters (i.e., along income distribution) vary across countries
  - interestingly the impact of crop diversification differs across country. Further analysis is required to show which specific crop leads to an increase in farmers competitiveness across countries